2018

Fiscal Pressures and Discriminatory Policing: Evidence from Traffic Stops in Missouri

Allison P. Harris
Pennsylvania State University - University Park

Elliott Ash
ETH Zürich

Jeffrey A. Fagan
Columbia Law School, jfagan@law.columbia.edu

Recommended Citation

Allison P. Harris, Elliott Ash & Jeffrey A. Fagan, *Fiscal Pressures and Discriminatory Policing: Evidence from Traffic Stops in Missouri*, JOURNAL OF RACE, ETHNICITY & POLITICS, VOL. 5, P. 450, 2020; COLUMBIA PUBLIC LAW RESEARCH PAPER NO. 14-591 (2018).
Available at: https://scholarship.law.columbia.edu/faculty_scholarship/2316

The Journal of Race, Ethnicity, and Politics, page 1 of 31, 2020.

doi:10.1017/rep.2020.10 2056-6085/20

Fiscal Pressures and Discriminatory Policing: Evidence from Traffic Stops in Missouri

Allison P. Harris
Yale University

Elliott Ash
ETH Zurich

Jeffrey Fagan
Columbia University

Abstract: This paper provides evidence of racial variation in traffic enforcement responses to local government budget stress using data from policing agencies in the state of Missouri from 2001 through 2012. Like previous studies, we find that local budget stress is associated with higher citation rates; we also find an increase in traffic-stop arrest rates. However, we find that these effects are concentrated among White (rather than Black or Latino) drivers. The results are robust to the inclusion of a range of covariates and a variety of model specifications, including a regression discontinuity examining bare budget shortfalls. Considering potential mechanisms, we find that targeting of White drivers is higher where the White-to-Black income ratio is higher, consistent with the targeting of drivers who are better able to pay fines. Further, the relative effect on White drivers is higher in areas with statistical over-policing of Black drivers: when Black drivers are already getting too many fines, police cite White drivers from whom they are presumably more likely to be able to raise the needed extra revenue. These results highlight the relationship between policing-as-taxation and racial inequality in policing outcomes.

Keywords: policing, traffic stops, discrimination, budgets, local budgets, budgetary, shortfalls, racial discrimination.

Address correspondence and reprint requests to: Allison P. Harris, Yale University, New Haven, Ct, USA. E-mail: allison.harris@yale.edu

INTRODUCTION

New models of policing combining aggressive tactics with data-driven management metrics have created tensions between the residents of low-income communities—often home to members of racial and ethnic minority groups—and the police (Heymann 2000; Tyler and Fagan 2008), with little evidence of substantial public safety gains (MacDonald, Fagan, and Geller 2016). In this article, we examine how institutional changes can affect racially targeted policing, where historically traffic and misdemeanor enforcement has been concentrated among drivers and residents in communities subjugated by race and class (Soss and Weaver 2017). Our goal is to provide evidence on how the institutional priorities of law enforcement agencies influence racial disparities in policing activities, which could potentially lead to the reproduction of disadvantage among heavily policed populations.

A large literature has documented that traffic police disproportionately target Black and Latino drivers when making stops (Pierson et al. 2017). At the micro level of individual traffic stops, scholars have formalized conditions for measuring discrimination, and econometricians and political scientists have identified it in traffic stop data (e.g. Grogger and Ridgeway 2006; Knowles, Persico, and Todd 2001; Rojek, Rosenfeld, and Decker 2004; Soss and Weaver 2017). At the macro level, the consequences of this discrimination have been observed in entire criminal justice systems, entire communities, and entire states (Baumgartner, Epp, and Shoub 2018; Fagan and Ash 2017; Shoub et al. 2020). More specifically, for example, Shoub et al. (2020) analyze a unique dataset covering multiple municipalities and control for a variety of stop-related and contextual factors to find that driver race remains an important predictor for whether a driver is searched. In this paper, we ask how shifting institutional motivations—that appear, on the surface, to be race-neutral—influence racial discrimination in traffic stops.[1]

A baseline motivation for policing is the desire to establish "social control" within poor communities of color (Soss and Weaver 2017). The advent of "law and order" policing in the 1960s and successive Wars on Crime continue to influence modern-day policing (Council 2004; Hinton 2016; Soss and Weaver 2017; Wilson and Kelling 1982). Officers motivated to quell urban "disorder" are more likely to police residents in poorer communities of color, contributing to racially disparate outcomes in traffic stop and street encounters.

However, another line of research has examined the public-finance motivations underlying aggressive policing. It is well-documented that local governments rely on revenue from traffic tickets, and officials often look to this source of revenue to help overcome budget shortfalls (DOJ 2015). In fact, some jurisdictions structure revenues that they anticipate from fines, fees, and seizures into agency budgets (Baicker and Jacobson 2007). Other jurisdictions pursue these revenue-generating activities not only to provide municipal services, but to sustain their own police forces. For example, the recent Ferguson Report issued by the U.S. Department of Justice suggests that the municipality tried to cloak its taxing power in the exercise of police power by functionally equating the power of taxation with the power to punish (DOJ 2015). The report noted that local police in Ferguson and nearby communities had grown to depend on these revenue streams to sustain the size of the police force and to pay salaries and annual increases to the officers. Significant racial differences in traffic stops persist 5 years after the protests in Ferguson (and 4 years after the DOJ Report),[2] illustrating how deeply embedded these practices are in the political and institutional culture.

In this paper, we explore, empirically, the intersection of race, policing, and this use of fees and fines as a form of latent taxation. We hope to shed light on how law enforcement's fiscal pressures interact with its treatment of members of different racial groups, often leading to a set of monetary burdens on those most closely surveilled and least likely to have the financial resources to shoulder those burdens. We use data from the state of MO to assess whether police officers' ticketing behaviors are discriminatory, whether the disparity in ticketing changes when a municipality is faced with governmental pressures to increase ticketing revenue, and what these changes may suggest about law enforcement's preferences when it comes to race and punishment.

To provide empirical evidence on these issues, we construct a dataset on local fiscal stress for 196 local policing agencies in MO from 2001 to 2012. When local governments experience negative budgetary shocks (shortfalls), police may be given incentives to increase traffic enforcement to generate revenue (Garrett and Wagner 2009), or to shift resources to enforcement activities more likely to generate revenue. We use traffic enforcement and arrest data to assess the effects of fiscal pressure. Our innovation from the previous literature on the relationship between fiscal distress and policing is that we consider effects across different groups of drivers.

Consistent with research on social control, discrimination, and policing, we find that traffic police in MO stop Black and Latino drivers more frequently than White drivers, as a share of the local population. However, we find that in times of budget stress, local police and sheriffs increase their targeting of White drivers. Holding the number of traffic stops constant, the citation rate and arrest rate for White drivers increase. There is no effect on citations and arrests of non-White drivers. The finding is robust to a number of alternative specifications and checks, and it does not appear to be driven by confounding trends. The result holds in a regression-discontinuity (RD) framework where, if a locality barely has a revenue shortfall, there is an increase in citation rates for White drivers but not for Black and Latino drivers.

These results may reflect a different set of institutional pressures regarding law enforcement and race than those that produce or increase racial discrimination, such as baseline commitments to social control or pressures related to the electoral cycle (Kubik and Moran 2003; Park 2017; Soss and Weaver 2017). Instead, the results are consistent with a model where traffic police selectively target presumably higher-income drivers to compensate for budget stress. Rather than being responsive to traditional discriminatory pressures—whether they arise from taste-based preferences, statistical discrimination, or institutional priorities—officers' increased citation and arrest rates of White drivers may be indicative of a shift toward targeting motorists where there is more scope for increased revenues.

We explore two key reasons for a White–Black difference in expected profitability. First, White drivers may have higher incomes than Black drivers and therefore be more likely to be able to pay fines. To probe this possibility, we examine whether our estimates depend on the ratio of incomes of White residents to Black residents in the local community. Indeed, we find that the targeting of White drivers in citation and arrest rates is most prevalent where the White-to-Black income ratio is highest. Therefore, the evidence supports relative income across drivers as a significant factor in revenue-generating policing decisions, specifically during times of municipal fiscal distress.

A second potential explanation is that targeting of White drivers is a side effect of pre-existing over-policing in Black communities. That is, Black drivers may already be getting stopped and cited as much as possible, so stopping an additional Black driver is unlikely to produce a revenue-generating ticket (because there are not enough additional Black drivers committing citable traffic violations, or who are willing or able to pay). We find evidence consistent with this mechanism: targeting White drivers under fiscal pressure is highest in areas with the highest Black stop intensity (stops of Black drivers per Black resident). In other words, our findings suggest that when pressed to find new revenue streams to self-finance policing, discriminatory policing shifts from the usual targets of social control (Black drivers with relatively limited economic resources) to relatively high-income White drivers (normally the lowest-priority targets for social control through policing).

BACKGROUND

Racial disparities in traffic stops and citations are widespread in MO (Hernández-Murillo and Knowles 2004; Missouri 2019; Rojek, Rosenfeld, and Decker 2004; Rosenfeld, Rojek, and Decker 2011) and elsewhere (Baumgartner, Epp, and Shoub 2018; Epp, Maynard-Moody, and Haider-Markel 2014; Harris 1999; Pierson et al. 2017). Earlier research on discriminatory enforcement in highway searches suggested two alternative explanations. Either police were stopping people of color more often because they were more likely to have drugs or contraband (what economists refer to as statistical discrimination), or police were stopping these motorists more often because of their preferences for stopping people of color (what economists refer to as taste-based discrimination) (Gross and Barnes 2002; Knowles, Persico, and Todd 2001; Persico and Todd 2006). In practice, it can be difficult to identify whether or not individual officers, who are constrained actors in large and complex governmental institutions, have a "taste" for discrimination. However, research has also shown that even though they are searched and stopped at higher rates than Whites, stops of Black and Latino drivers are often less likely to result in the discovery of contraband (Goel et al. 2017; Stanford Open Policing Project 2019). Such findings mirror those from analyses of stop-and-frisk and similar policies, where Blacks and those in poor neighborhoods are stopped and frisked more frequently than Whites, but less likely to be found in possession of contraband, suggesting discrimination based on perceived racial identity (Fagan et al. 2009; Harcourt 2008; Soss and Weaver 2017).

Racial discrimination in traffic stops is consistent with a police force motivated by a desire to establish "social control" (Soss and Weaver 2017) within poor communities of color. The advent of "law and order" policing in the 1960s and the Wars on Crime and Drugs has had long-lasting effects (Harmon 2012; Hinton 2016; Soss and Weaver

2017; Wilson and Kelling 1982). The models of policing that have emerged since then and through the 2000s continue to share a commitment to "the elimination of disorder and the regulatory enforcement of codes against disordered people and places" (Soss and Weaver 2017, 570) and have contributed to community views of the police as an oppressive institution (Weaver, Prowse, and Piston 2020). As long as such "disorder" is associated with poor communities of color, we should continue to expect to observe racially disparate policing outcomes, including those stemming from traffic stops.

The interactions between racial discrimination in policing and the pressure on officers to maximize revenue are complex. Monetary penalties have proven to be quite popular in state legislatures and in criminal legal institutions. Fines are seen both as a legitimate deterrent to wrongdoing and a means of transferring the costs of criminal justice administration (courts, police, prisons, etc.) to those accused of breaking the law, costs that would otherwise fall on ostensibly law-abiding taxpayers. In addition, unlike prison, fines do not keep the defendant out of the workforce. However, these fines and related fees (including late payment fees and court fees) can act as a latent tax on poor people (Bannon, Nagrecha, and Diller 2010; CEA 2015; Harris 2017). Traffic stops can provide a politically expedient mechanism to generate revenue since the related fines and fees allow state and local legislators to get around tough rules limiting local tax increases. Fines and administrative fees offer the executive a path to budgetary relief with limited legislative involvement or court oversight, allowing for de facto taxation by administrative rulemaking.

Recent studies, such as the DOJ Ferguson Report (DOJ 2015), provide evidence of this instrumental motivation for police to pursue traffic stops: maximizing revenue to police agencies to sustain or expand police budgets. The Ferguson Report (2015) also illustrates how this revenue-generating regime disproportionately penetrates communities with high proportions of people of color. Disparate treatment at each stage of processing skews the criminal justice "tax" toward Blacks and Latinos, whose economic position often is more tenuous than that of their White counterparts (Parker, Lane, and Alpert 2010). The case of Ferguson is part of the broader geography of racial targeting in aggressive policing (Fagan and Ash 2017; Geller et al. 2014).

Police departments are often encouraged to maintain revenues from fines and fees at the expected level, and local executives have even reminded police departments that these revenues directly affect officers' pay. For example, in the Appendix, we include an infamous memo by

Mayor John Gwaltney of Edmundson, MO, encouraging the local police department to write more tickets. In the letter, the mayor reminds the police department that "the tickets [officers] write do add to the revenue on which the [police department] budget is established and will directly affect pay adjustments at budget time."

Research has shown that the kind of budgetary priorities expressed in Mayor Gwaltney's memo do impact officers' behavior, but that impact does not necessarily overpower any racial biases or preferences that may be driving officers' behavior. For example, Makowsky and Stratmann (2009) use MA traffic citation data to find that officers' budget-maximizing behaviors are shaped by political considerations as well as preferences regarding race and gender. Even critics of the evidence of racial bias in revenue-focused policing acknowledge the pressure on local institutions to focus enforcement on those perceived as "outsiders" (Heriot 2017). Most recently, Goldstein, Sances, and You (2018) analyze data from over 5,000 local governments and find that municipalities relying on fines and fees as a greater share of revenue have lower violent and property crime clearance rates, as police departments' energies are directed toward revenue-generating activities. Rather than competing motivations of social control versus revenue maximization, revenue generation and race-based policing seem to exist in an equipoise.

The use of arrest- or ticketing-generated revenues to offset budget shortfalls is hardly confined to MO (Sobol 2016). For example, Garrett and Wagner (2009) find that police in NC issued more tickets after local revenue shortfalls, and Rowe (2010) finds that discrimination against out-of-town drivers in traffic enforcement by police in MA is motivated by revenue shortfalls. Baicker and Jacobson (2007) show that laws permitting police seizures of money incentivized police to increase drug arrest activities, leading to a tug-of-war between police and local public finance authorities. Surveying this literature, the Council of Economic Advisers (2015) concluded that "[i]ncreases in criminal justice spending have put a strain on local criminal justice budgets and led to the broader use of fine[s], penalties, and itemized criminal justice fees in an effort to support budgets."

We seek to identify the types of drivers officers target when given increased incentives to bring in revenue. If baseline traffic stop, citation, and arrest rates are disparate across drivers' racial identities, a change in officers' incentive structure could result in shifts in those disparities. For example, Gordon and Huber (2007) show that when trial judges are up for election, they issue harsher criminal sentences, and Berdejo and

Yuchtman (2013) show that criminal sentences are 10% longer as judges approach the end of their electoral cycle. Park (2017) finds that this electoral-pressure effect is disproportionately focused among Black defendants. Relatedly, Kubik and Moran (2003) find that states are approximately 25% more likely to conduct executions in gubernatorial election years than in other years, and that there is a larger effect on the probability that a Black defendant will be executed than on the probability that a White defendant will be executed. Recent work shows that these electoral cycles may not be widespread, being most pronounced in the small set of states from which data for previous studies were collected (Dippel and Poyker 2019). However, Dippel and Poyker (2019) also find that electoral cycles may be most likely in states with high levels of electoral competition among judges.

This paper aims to identify how institutional enforcement incentives affect racial disparities in police traffic stops. The Ferguson Report (2015) found evidence of fiscal enforcement motives within the courts, city government, and the police, in particular; the interaction of these fiscal motives with traffic officers' decision making may provide additional insights about the structure of discriminatory policing. If police are responsive to fiscal pressures and aware that shifting resources away from racially discriminatory stops may result in higher revenue, we might expect to see a shift of officers' attention away from Black and Latino drivers and toward White drivers, who may be relatively more able to pay the related fines. In other words, during times of municipal fiscal distress, officers might prioritize the incentive to bring in revenue (that could be directed toward their department and their own salaries) over baseline preferences for discriminatory policing, or at least attempt to balance the two.

One possibility is that the political economy of local policing makes it more costly for law enforcement to impose the latent taxation of consistent traffic citations on higher income motorists who may have more political influence; to the extent that officers use race as a proxy for this influence, they may target non-White drivers for consistent enforcement. Even if less well-off Black and Latino drivers have less ability to pay on average, targeting them consistently may maximize long-run revenues if their relative lack of political power and resources (compared to Whites) prevents them from effectively challenging discriminatory enforcement. Higher income, disproportionately White, motorists may serve as a ready source of additional revenue in the short run, specifically in times of fiscal distress. Although the individual racial preferences of officers are likely to impact enforcement discrepancies (Donohue and Levitt 2001), as are the institutional decisions within each police department, revenue-maximizing policing may also be guided by the different revenue elasticities of enforcement that local officials expect to encounter among groups with varying political power (Makowsky, Stratmann, and Tabarrok 2018).

DATA

The paper merges two main datasets for the analysis. The first is the local government finances data for MO, from which we construct a measure of budget distress. The second is the agency-level traffic stops data, used to construct measures of traffic enforcement effort across racial groups. There are 769 agencies in the dataset, for which we have 13 years of annual panel data from 2000 through 2012. We also include a variety of municipal- and county-level census demographic measures.

The data on local government financial accounts come from the IndFin local government finances census dataset. The accounts data include items on revenues, expenditures, assets, and liabilities. The data are matched to municipal governments (police departments) and county governments (sheriff's departments).

IndFin is a survey of all local governments administered every 5 years; if the localities do not provide previous years' data, those values are imputed by the Bureau of Census statisticians. This induces measurement error but should not bias the estimates away from zero in either direction. There are some missing data in the census, which we partly filled in using annual financials directly from the state of MO.

Our preferred measure of local fiscal distress is based on Garrett and Wagner (2009). We have the log government revenue for agency i at year t, G_{it}. In the regression models that follow, our measure of *Fiscal Distress* at year t is the proportional change in log revenue for the *previous* year, ΔG_{it-1}. This is meant to summarize the idea that there is a revenue problem that is realized at the end of the year, which the government may try to make up for the next year through increased ticketing. The reason for using revenues, without including expenditures, is that they are not as easily changed by local government, and therefore an exogenous "end of year" effect on policing decisions is more plausible. Still, we have tried using expenditures minus revenues as an alternative measure for fiscal distress, and our main results are the same.[3]

In addition, we include a RD specification where we look at discrete changes in policing around the threshold of a negative budget change.

For the RD specification, the variable *Budget Shortfall* is defined as $\Delta G_{it-1} < 0$; that is, it equals one if revenue collections went down last year. We tried an "in-the-red" specification where treatment is years where expenditures were higher than revenues, but we found no effects in that specification.

The data on traffic stops come from the MO Attorney General's Racial Profiling database. This is an annual survey of policing agencies that includes a distribution across race and ethnicity for all traffic policing actions. MO has been collecting statewide incident-level data on police traffic stops since 2001. The form that agencies have to fill out for every traffic stop is included in the Appendix. We have access to aggregate data, by agency and the race/ethnicity of the person stopped, for the years 2001 through 2013, and use the years 2001 through 2012. Hernández-Murillo and Knowles (2004), Rojek, Rosenfeld, and Decker (2004), and Rosenfeld, Rojek, and Decker (2011) all have used these data to analyze aggregate racial disparities in traffic stops at different points in time.

The merged traffic stop and finance data include over 700 of MO's counties and cities, while smaller municipalities, such as villages, are not included. We do not include these smaller municipalities, because they are difficult to merge with finance data (they may be less likely to respond to the IndFin survey, municipality names were less consistent for these locations, and some municipalities cross county borders). However, these smaller municipalities have far fewer traffic stops than those included in the dataset, and they also typically have populations that are less diverse, racially. The local finance data are available for most of the sheriffs and police departments in the dataset for the years 2002, 2007, and 2012 when the IndFin survey was conducted, with more departments responding in 2007 and 2012 than in 2002. In non-survey years, we have finance data for 196 departments, including 69 sheriff's departments and 127 police departments.[4]

The main variable of interest from IndFin is log revenue changes. We use the log revenue change for the previous year as a sign of fiscal health. The distribution of this variable is included in the Appendix. We do not see any sign of manipulation of revenues around the zero cutoff.

Finally, we collected and merged in a range of demographic variables from the American Community Survey (ACS), matchable to county or municipality. We use the ACS 3-year estimates that span the time period included in this study. These variables include the 2000 (pre-analysis) values for log population, proportion white-race residents, proportion urban vs rural, and proportion aged over 65. We use these as controls, interacted with year, and we also use them in heterogeneity analyses, included below.

We focus on four outcome variables constructed from the racial profiling data. First, we compute the **citation rate**, which is the number of citations issued by agency i to drivers of race r during year t, divided by the number of total traffic stops by agency i of drivers of race r during year t. Similarly, the **search rate** is the number of searches divided by the number of stops. The **hit rate** is the number of contraband discoveries divided by the number of searches. The **arrest rate** is the number of arrests divided by the number of stops. Summary statistics for these measures, by race, are reported in Table 1. We also report the stops per person, where the numerator is total stops for a racial/ethnic group and the denominator is the local population identifying with that racial/ethnic group from the 2000 and 2010 censuses, with the intervening years interpolated.

There are few differences by race or ethnicity in the citation rates. However, search and arrest rates are significantly higher for Black and Latino motorists. The patterns in search and arrest rates are in line with those found nationwide; Black and Latino drivers are searched more frequently than White drivers and Latino drivers experience even higher search rates than Blacks (Pierson et al. 2017). The hit rate is highest for Whites, suggesting preferential treatment for Whites in searches on average (e.g. Hernández-Murillo and Knowles 2004). Finally, there are big differences in stops per person, with Blacks having an especially high number of stops per person on average.

To assess the statistical significance of these baseline differences, we estimate the following multivariate regression:

$$Y_{irt} = \alpha_{it} + \gamma_0 \mathrm{Black}_{irt} + \gamma_1 \mathrm{Hispanic}_{irt} + X'_{irt}\beta_{it} + \varepsilon_{irt}, \tag{1}$$

where α_{it} is an agency-year fixed effect, Black_{irt} is a dummy variable equaling one for Black drivers, and $\mathrm{Hispanic}_{irt}$ is a dummy variable equaling one for Latino drivers. We run this regression for Black, Latino, and White drivers, so γ_0 and γ_1 give the average differences of Blacks and Latinos from Whites, after residualizing out the fixed effects and controls.

We have access to a range of covariates, represented in X_{irt}, which again are aggregated by race. For driver demographics, we have age (proportion of drivers in bins 18–29, 30–39, and 40+) and gender (proportion male). We have the location (city-street, county road, interstate, state highway, U. S. highway) of the stop, reason for the stop (e.g. moving violation), and the authority given for a search (consent, drug/alcohol odor, drug dog alert, incident to arrest, inventory, plain view, or reasonable suspicion). We

Table 1. Summary Statistics on Stop Outcomes by Race

		Counts (by Agency-Year)						Rates			
Race		Stops	Citations	Searches	Hits	Arrests	Stops per Person	Citation	Search	Hit	Arrest
Asian	Mean	33.732	20.67	1.074	.163	.744	1.73	.4778	.0414	.1625	.0299
	S.D.	144.842	99.041	5.402	.875	3.219	9.3	.4051	.1309	.3255	.1115
Black	Mean	450.598	295.789	51.634	9.092	38.642	3.82	.4649	.1105	.2236	.0826
	S.D.	2,760.000	1,780.000	321.317	56.630	237.992	18.6	.3275	.1434	.2963	.1325
Latino	Mean	60.874	38.622	7.977	1.170	5.675	1.26	.4984	.1361	.1686	.0960
	S.D.	394.418	285.101	41.714	6.478	29.628	14.5	.3493	.1886	.2753	.1637
White	Mean	1,920.000	1,090.000	124.945	28.843	86.646	.465	.4636	.0797	.2790	.0543
	S.D.	12,600.000	7,970.000	629.777	159.255	469.428	3.12	.2733	.0829	.2287	.0723
Other	Mean	30.728	17.716	1.430	.257	.883	2.24	.4740	.0623	.19780	.0427
	S.D.	141.959	99.115	6.247	1.186	3.714	33.5	.3849	.1600	.3399	.1355

also include the reason for arrest—drug violation, driving while intoxicated, assault, outstanding warrant, property crime, resisting arrest, and traffic violation.

The results from estimating Equation (1) are reported in Table 2. The first striking thing is that Blacks have *many* more stops relative to their share of the population (columns 1 and 2) than members of other racial/ethnic groups. This much higher stop rate likely explains the, perhaps surprising, result that Black drivers tend to have a *lower* citation rate than White drivers (columns 3 and 4); many more Black drivers are stopped, including many who do not deserve a ticket. Meanwhile, Latino drivers are cited at a significantly higher rate. Both Blacks and Latinos are searched at a higher rate, with lower contraband hit rates, than Whites. Both Blacks and Latinos are arrested at higher rates than Whites. In particular, the lower rate of productive searches for Blacks and Latinos (columns 7 and 8) suggests that police are more careful and selective in searching White motorists compared to non-White drivers (e.g. Hernández-Murillo and Knowles 2004).

EMPIRICAL STRATEGY

This section describes the approach for analyzing the relationship between local budget stress and discriminatory policing. The research design is based on that employed by Garrett and Wagner (2009), who found, using data from 1990 through 2003, that NC municipalities with negative budget shocks responded by issuing more traffic tickets. The main goal, here, is to measure the disparate racial impacts of budget response by policing agencies.

We estimate the racial disparity in the change in enforcement outcome Y_{irt} (e.g. the citation rate) for agency i, race r, and year t using

$$\Delta Y_{irt} = \alpha_{ir} + \alpha_{rt} + \sum_{s} \rho_s R_{r=s} D_{it} + X'_{irt}\beta + \varepsilon_{irt} \tag{2}$$

where α_{ir} is an agency-race interacted fixed effect, α_{rt} is a race-year interacted fixed effect, and is an error term. The treatment variable D_{it} is a measure for fiscal distress, defined as the negative change in revenue for the previous year in jurisdiction i. This measure, called *Fiscal Distress* in the tables below, is based on Garrett and Wagner (2009). The term $R_{r=s}$ is a dummy variable for the race of the driver, and the term ρ_s gives the impact of lagged fiscal distress on race $s \in \{White, Black, Hispanic\}$. Therefore, the summation expression in (2) gives three

Table 2. Racial Differences in Stop Outcomes: Regression Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Stops per Person		**Citation Rate**		**Search Rate**		**Hit Rate**		**Arrest Rate**	
Black Driver	3.595**	3.720**	−.00700+	−.0101**	.0296**	.00294**	−.0343**	−.0312**	.0274**	.00908**
	(.759)	(.827)	(.00359)	(.00376)	(.00207)	(.000886)	(.00471)	(.00582)	(.00187)	(.00135)
Latino Driver	.432	.789	.0238**	.0211**	.0549**	.00576**	−.0894**	−.0943**	.0400**	.0186**
	(.595)	(.815)	(.00498)	(.00583)	(.00284)	(.00116)	(.00469)	(.00897)	(.00265)	(.00201)
Agency-Year FE's	X	X	X	X	X	X	X	X	X	X
Demographics		X		X		X		X		X
Stop Reasons		X		X		X		X		X
Search Reasons						X		X		
Arrest Reasons										X
N	10,249	10,249	21,777	21,777	21,802	21,802	14,216	14,216	18,591	18,591
R^2	.120	.118	.612	.623	.274	.880	.240	.282	.300	.696

Notes: Observation is an agency-race-year, where Whites, Blacks, and Latinos are included. Standard errors in parentheses, clustered by agency. $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$.

effects: of fiscal distress on the outcome, separately for each of the three driver races. If local governments in budgetary distress seek to impose a larger share of taxes on members of a racial group, that would be consistent with $\hat{\rho}_r > 0$.

We cluster standard errors by policing agency to allow for serial correlation across time in the agencies. The identification assumption for unbiased OLS estimates of ρ is that D_{it} is uncorrelated with other unobserved factors affecting the rates of change in the outcome in period t, conditional on the fixed effects. This may be a strong assumption if last year's budget conditions influence other socioeconomic and/or political factors this year that in turn affect traffic ticketing. An example of this type of factor would be decreases in expenditures on traffic lights and road signs, which may reduce ticketing. We assess the identification assumption by testing different specifications and adding controls. In addition, we include a RD specification where we look at discrete changes in policing around the budget shortfall threshold. For the RD design, the variable *Budget Shortfall* is a dummy variable equaling one when revenue collections decreased last year.[5]

RESULTS

This section reports results from a number of analyses. First, we consider a range of outcomes discussed in section "Data". We then provide regression estimates for ρ and ρ_r in Equation (2) from section "Empirical Strategy". We report a number of specification checks, and, then, consider heterogeneous effects based on the characteristics of the jurisdictions.

Main Results

The first regression estimates are reported in Table 3. We look at four outcomes: citation rate, search rate, hit rate, and arrest rate, defined in section "Data". The tables include our baseline specifications (with agency-race and race-year fixed effects) in columns 1, 3, 5, and 7. The other columns (2, 4, 6, 8) include a number of stop-related covariates for the demographics of drivers arrested, and the reasons for stops, searches, and arrests, which may be correlated with driver race and subsequent outcomes. The rows give the interacted effects for White, Black, and Latino drivers, respectively. The sample includes White, Black, and Latino drivers.

Table 3. Effect of Fiscal Distress on Enforcement Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Citation Rate		**Δ Search Rate**		**Δ Hit Rate**		**Δ Arrest Rate**	
Fiscal Distress	.0548**	.0481*	.0259+	.0027	.00239	−.0076	.0347**	.0214*
×White Driver	(.0207)	(.0195)	(.0136)	(.0104)	(.0311)	(.0321)	(.0121)	(.0096)
Fiscal Distress	−.0145	−.00693	−.0171	−.0170	.0131	.00794	−.0342	−.0175
×Black Driver	(.0323)	(.0328)	(.0301)	(.0283)	(.0616)	(.0578)	(.0385)	(.0261)
Fiscal Distress	.00350	−.00405	.0841+	.0555+	.0199	.0267	.0717*	.0368
×Latino Driver	(.0396)	(.0410)	(.0475)	(.0283)	(.0590)	(.0566)	(.0360)	(.0249)
Agency-Race FE's	X	X	X	X	X	X	X	X
Race-Year FE's	X	X	X	X	X	X	X	X
Demographics		X		X		X		X
Stop Reasons		X		X		X		X
Search Reasons				X		X		
Arrest Reasons								X
N	3,361	3,361	3,363	3,363	2,978	2,978	2,612	2,612
R^2	.115	.193	.067	.505	.103	.154	.088	.497

Notes: Observation is an agency-race-year, where Whites, Blacks, and Latinos are included. *Fiscal Distress* is defined as the log negative revenue change. ×*Black Driver* and ×*Latino Driver* indicate the interaction between *Fiscal Distress* and dummy variables for the respective driver race. Standard errors in parentheses, clustered by agency. $^{+}p<.10$, $^{*}p<.05$, $^{**}p<.01$.

We find, first, that a decrease in government revenue growth the previous year is associated with a higher citation rate for White drivers (columns 1 and 2). The estimates are not statistically significant for Latino drivers or for Black drivers. There is a statistically significant increase in the arrest rate for White drivers as well, but not for Black or Latino drivers. Finally, a decrease in government revenue growth does not have much effect on the search rate or hit rate. However, there is a marginally significant positive relationship with the search rate for Latino drivers.

Next, in Table 4, we further probe the results for citation rates. First, we present results from separate models for each racial group. We see that there is a positive relationship between fiscal distress and citation rate for White drivers (column 1), but not for Black (column 2) or Latino (column 3) drivers. The results for Whites alone (column 4) are robust to adding a set of pre-treatment census demographic controls (total population, percent White, percent urban, and percent over 65), interacted with a full set of indicators for each year in our data. The estimates with all three races included are not significant (column 5). An alternative specification (column 6) including White drivers in the baseline, and Blacks/Latinos interacted, shows that the interactions, while negative, are noisy and not statistically different from White drivers.

Table 5 includes similar robustness checks for arrest rates. Again, we see a positive relationship between fiscal distress and arrest rates for Whites, but not for Black or Latino drivers. These coefficients are robust to the full set of census covariates interacted with each year in the data. Overall, these results support the view that in response to budget stress, MO police are arresting White drivers more often. One interpretation of this evidence is that officers expect that arrests of White drivers would generate more revenue through the legal financial obligations that stem from an arrest.

In Table 6, we look at the change in counts, rather than rates, to see what components of our variables are changing in response to the budget distress. First, we check whether these results are driven by changes in total stops (versus changes in total citations, e.g.). We can see from columns (1) and (2) that the results are not driven by changes in total stops, which remain unchanged during times of fiscal distress. These estimates are also zero if looking at stops per person, dividing by the local race population. The coefficients for White drivers on number of citations, searches, search hits, and arrests are all positive, but significant only for arrests. While it is only significant at the 10% level, there is a

Table 4. Robustness: Effect of Fiscal Distress on Citation Rates

	(1)	(2)	(3)	(4)	(5)	(6)
			Effect on Δ Log Citation Rate			
Fiscal Distress (Baseline)	.0471* (.0207)	−.0141 (.0347)	−.00864 (.0421)	.0492* (.0211)	.0122 (.0224)	.0510* (.0197)
Fiscal Distress ×Black Driver						−.0620 (.0378)
Fiscal Distress ×Latino Driver						−.0603 (.0447)
Sample	Whites	Blacks	Latinos	Whites	All	All
Agency-Race FE's	X	X	X	X	X	X
Race-Year FE's	X	X	X	X	X	X
Demographics	X	X	X	X	X	X
Stop Reasons	X	X	X	X	X	X
Census×Year FE's				X	X	X
N	1,190	1,109	1,062	1,159	3,293	3,293
R^2	.189	.251	.190	.216	.227	.228

Census×Year FE's means pre-2001 local demographics (population, % white, % urban, and % over 65) interacted with year fixed effects.
Notes: Observation is an agency-race-year, where Whites, Blacks, and Latinos are included. *Fiscal Distress* is defined as the log negative revenue change. ×*Black Driver* and ×*Latino Driver* indicate the interaction between *Fiscal Distress* and dummy variables for the respective driver race. Standard errors in parentheses, clustered by agency. $^{+}p<.10$, $^{*}p<.05$, $^{**}p<.01$.

Table 5. Robustness: Effect of Fiscal Distress on Arrest Rates

	(1)	(2)	(3)	(4)	(5)	(6)
			Effect on Δ Log Arrest Rate			
Fiscal Distress	.0223*	−.00873	.0311	.0215*	.0127	.0214*
(Baseline)	(.00862)	(.0212)	(.0230)	(.00890)	(.0133)	(.00975)
Fiscal Distress						−.0409
×Black Driver						(.0278)
Fiscal Distress						.0132
×Latino Driver						(.0279)
Sample	Whites	Blacks	Latinos	Whites	All	All
Agency-Year FE's	X	X	X	X	X	X
Race-Year FE's	X	X	X	X	X	X
Demographics	X	X	X	X	X	X
Stop Reasons	X	X	X	X	X	X
Census×Year FE's				X	X	X
N	921	854	837	895	2,559	2,559
R^2	.579	.569	.517	.518	.519	.520

Census×Year FE's means pre-2001 local demographics (population, % white, % urban, and % over 65) interacted with year fixed effects.
Notes: Observation is an agency-race-year, where Whites, Blacks, and Latinos are included. *Fiscal Distress* is defined as the log negative revenue change. ×*Black Driver* and ×*Latino Driver* indicate the interaction between *Fiscal Distress* and dummy variables for the respective driver race. Standard errors in parentheses, clustered by agency. $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$.

Table 6. Effect of Fiscal Distress on Enforcement Counts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Δ Log Total Stops		Δ Log Citations		Δ Log Searches		Δ Log Search Hits		Δ Log Arrests	
Fiscal Distress	−.0674	−.0845	.143	.127	.214	.0963	.129	.0697	.521**	.429**
×White Driver	(.102)	(.102)	(.124)	(.123)	(.160)	(.141)	(.153)	(.153)	(.162)	(.149)
Fiscal Distress	−.208	−.214	−.238^{+}	−.237^{+}	−.0941	−.158	−.139	−.221	.163	.267^{+}
×Black Driver	(.157)	(.144)	(.128)	(.131)	(.167)	(.156)	(.168)	(.160)	(.166)	(.160)
Fiscal Distress	−.0253	−.0584	.0285	−.0318	.281	.0754	.180	.0682	.393^{+}	.231
×Latino Driver	(.151)	(.153)	(.156)	(.160)	(.202)	(.183)	(.161)	(.156)	(.228)	(.214)
Agency-Race FE’s	X	X	X	X	X	X	X	X	X	X
Race-Year FE’s	X	X	X	X	X	X	X	X	X	X
Demographics		X		X		X		X		X
Stop Reasons		X		X		X		X		X
Search Reasons						X		X		
Arrest Reasons										X
N	3,350	3,350	3,328	3,328	3,329	3,317	3,313	3,308	2,612	2,609
R^2	.114	.139	.121	.144	.092	.255	.089	.154	.108	.271

Notes: Observation is an agency-race-year, where Whites, Blacks, and Latinos are included. *Fiscal Distress* is defined as the log negative revenue change. ×*Black Driver* and ×*Latino Driver* indicate the interaction between *Fiscal Distress* and dummy variables for the respective driver race. Standard errors in parentheses, clustered by agency. $^{+}p<.10$, $^{*}p<.05$, $^{**}p<.01$.

statistical decrease in the number of citations given to Black drivers, consistent with re-allocation across races.

Overall, the results of the analysis of counts substantiate the main finding that fiscal distress changes the number of citations assigned to and number of arrests of White drivers. There is no effect on the number of traffic stops for White drivers or non-White drivers, meaning that officers are not replacing stops of Black drivers with stops of White drivers. Rather they appear to be treating the same set of White drivers they normally stop more harshly. For Black drivers, the fact that stops are not increasing means that a decrease in citations and searches cannot be interpreted as an expansion in the sample of stopped drivers to a marginal set (drivers with relatively lower criminality). Instead, police seem to be re-allocating time away from the same set of drivers.

We report visual evidence of the relationship for citation rates in Figure 1, showing the RD jump for White, Black, and Latino drivers. The dependent variable, lagged change in log revenues, is on the x-axis. We mark the cut-off point at zero, with positive budget changes to the right and negative budget changes to the left. We can see a discrete change in citation activity at the zero revenue change cutoff. Just below the cutoff (a bare budget shortfall), we see a jump in citation rates for White drivers (left panel). For Black drivers, there are slightly fewer citations below the cutoff (middle panel). For Latino drivers, there is no difference (right panel). When there is a revenue shortfall, police in the subsequent year tend to target White drivers with traffic citations.

The regression results for this specification are in Table 7. First, we see in columns 1 and 2 that the main result for citation rates holds for an alternative definition for budget stress: a dummy variable equaling one if revenues decreased in the previous year. The table shows that if revenues decreased, the citation rate increases for White drivers but not for Black or Latino drivers. The effect of the dummy-variable treatment is robust to including the standard fiscal distress variable (lagged negative revenue change) as a control (columns 3–4). Here, the coefficient for the fiscal distress variable is not statistically significant, meaning that the citation rate change is driven by the discrete budget-shortfall effect. For arrests, we see the opposite. There is no discrete jump in enforcement at the revenue-negative cutoff. Instead, it is driven by the continuous Fiscal Distress variable (columns 7–8). The RD specification points to a causal relationship between budget shortfalls and racial differences in traffic citations.

Our main results on traffic citations are summarized graphically in Figure 2. The coefficient plots give the parameter estimates and

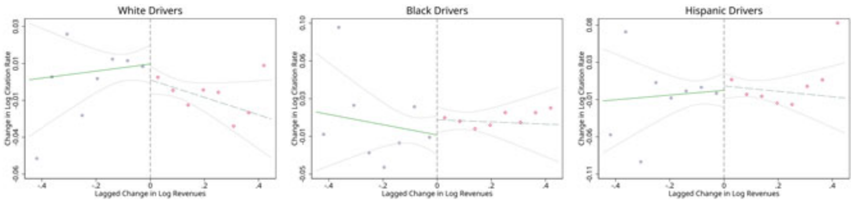

FIGURE 1. Regression Discontinuity: Effect of Negative Revenue Change on Citation Rates by Race. RD visualization for effect of the lagged local revenue change (horizontal axis) on change in log citation rates (vertical axis), separately by driver race/ethnicity. Graphs produced by "cmogram" package in Stata with *lfitci* option.

confidence intervals for the specifications in Table 3 column 2 (top panel, continuous treatment) and Table 7 column 2 (bottom panel, discrete treatment). The plots illustrate quite clearly how the effect of fiscal pressure on traffic citation behavior varies by the race of the stopped driver.

Heterogeneous Results

Table 8 considers the importance of the White–Black income ratio. Officers may increase citations and arrests of White drivers in response to fiscal distress because they expect that White drivers will have higher incomes than Black or Latino drivers and, therefore, be better able to pay the related fees, which will be used to address budgetary shortfalls. If this is the case, we should expect fiscal distress to lead to tougher treatment of stopped White drivers in areas where the income inequality between Whites and Blacks is highest. To test this, we split the sample by the White–Black income ratio. A high ratio represents greater income inequality between Whites and Blacks.

For White drivers, we see that, across specifications, there is generally a positive, significant relationship between budget shortfalls and fiscal distress and citation rates. However, the relationship with the continuous measure is not significant under a low White–Black ratio (column 1). In addition, the negative relationship between the discreet measure and citation rates for Black drivers is larger in magnitude, more precisely estimated, and statistically significant only for areas with above-median White–Black income inequality (see column 4). This result supports a model where officers are more likely to target White drivers in times of

Table 7. RD Specification: Revenue Reductions versus Budget Shortfall

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Citation Rate				**Δ Arrest Rate**			
Sample	**Whites**	**All**	**Whites**	**All**	**Whites**	**All**	**Whites**	**All**
Budget Shortfall ×White Driver	.0199** (.00704)	.0196** (.00673)	.0167+ (.00901)	.0160+ (.00887)	.00298 (.00466)	.00388 (.00477)	−.00572 (.00515)	−.00559 (.00531)
Budget Shortfall ×Black Driver		−.00555 (.0103)		−.00473 (.0132)		−.0149 (.0119)		−.0155 (.0129)
Budget Shortfall ×Latino Driver		.00346 (.0113)		.00418 (.0164)		.0161 (.0106)		.000385 (.0138)
Fiscal Distress ×White Driver			.0162 (.0268)	.0186 (.0272)			.0439** (.0138)	.0476** (.0143)
Fiscal Distress ×Black Driver				−.00428 (.0406)				.00271 (.0400)
Fiscal Distress ×Latino Driver				−.00369 (.0637)				.0803 (.0549)
Agency-Race FE's	X	X	X	X	X	X	X	X
Race-Year FE's	X	X	X	X	X	X	X	X
Demographics	X	X	X	X	X	X	X	X
Census×Year FE's	X	X	X	X	X	X	X	X
N	1,159	3,293	1,159	3,293	895	2,559	895	2,559
R^2	.146	.177	.146	.177	.113	.122	.120	.125

Census×Year FE's means pre-2001 local demographics (population, % white, % urban, and % over 65) interacted with year fixed effects.

Notes: Observation is an agency-race-year, where Whites, Blacks, and Latinos are included. *Budget Shortfall* is defined as an indicator equaling one if revenue changes were negative last year. *Fiscal Distress* is defined as the log negative revenue change. ×*Black Driver* and ×*Latino Driver* indicate the interaction between the indicate revenue variable and the respective driver race. Standard errors in parentheses, clustered by agency. $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$.

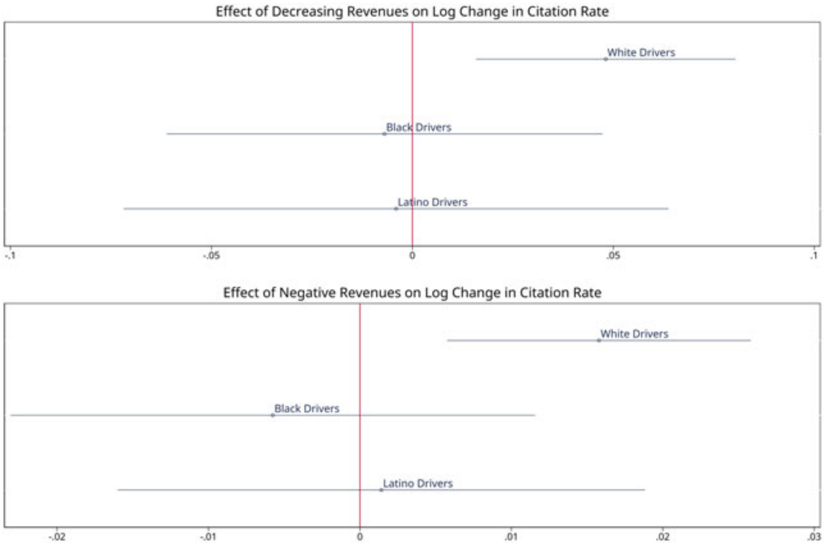

FIGURE 2. Coefficient Plots: Main Results for Citation Rates by Race. Coefficient plots for main regression results. Specifications are from Table 3 column 2 (top panel, *Fiscal Distress* continuous treatment), and Table 7 column 2 (bottom panel, *Budget Shortfall* discrete treatment). Outcome is log change in citation rate. Regression includes agency-race FE's, race-year FE's, driver demographics, and stop reasons.

fiscal distress when they have a higher expectation of White drivers' ability to pay.

For arrests, we see an increase for White drivers only when there is a high White–Black income ratio (columns 7–8). The interactions with Black driver are not significant, which could be more evidence that when Whites have higher incomes, police target them more frequently for arrest in order to generate legal financial obligations. Given constraints on the total number of traffic stops that can be made, police agencies under fiscal distress re-allocate citations and arrests to these higher-income drivers.

Finally, Table 9 presents the results from our second heterogeneity analysis on Black driver stop intensity. For this analysis, we explore the possibility that our results are driven by a selection effect of marginal drivers across races. At baseline, there could be significant over-policing of Black drivers, and the marginal driver is not committing any citable offenses. Therefore, the marginal value of stopping more Black drivers

Table 8. Heterogeneity by White–Black Income Ratio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Citation Rate				**Δ Arrest Rate**			
Fiscal Distress ×White Driver	.0597 (.0365)		.0582* (.0265)		−.000893 (.0257)		.0526** (.0198)	
Fiscal Distress ×Black Driver	.00353 (.0510)		−.0439 (.0524)		−.0211 (.0333)		−.0641 (.0842)	
Budget Shortfall ×White Driver		.0236* (.0114)		.0132^{+} (.00774)		−.00637 (.00803)		.0106^{+} (.00535)
Budget Shortfall ×Black Driver		−.0160 (.0191)		−.0333* (.0165)		−.000391 (.0118)		−.0301 (.0253)
Sample	Low W-B Ratio		High W-B Ratio		Low W-B Ratio		High W-B Ratio	
Agency-Race FE's	X	X	X	X	X	X	X	X
Race-Year FE's	X	X	X	X	X	X	X	X
Demographics	X	X	X	X	X	X	X	X
Stop Reasons	X	X	X	X	X	X	X	X
Arrest Reasons					X	X	X	X
Census×Year FE's		X		X		X		X
N	1,043	1,043	1,206	1,206	824	824	911	911
R^2	.254	.257	.264	.265	.216	.217	.130	.130

Census×Year FE's means pre-2001 local demographics (population, % white, % urban, and % over 65) interacted with year fixed effects.
Notes: Observation is an agency-race-year, where Whites and Blacks are included. *Fiscal Distress* is defined as the log negative revenue change. *Budget Shortfall* is defined as an indicator equaling one if revenue changes were negative last year. ×*Black Driver* and ×*Latino Driver* indicate the interaction between the indicate revenue variable and the respective driver race. Standard errors in parentheses, clustered by agency. $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$.

Table 9. Heterogeneity by Black Driver Stop Intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Citation Rate				**Δ Arrest Rate**			
Fiscal Distress ×White Driver	.0599^{+} (.0342)		.0675^{+} (.0376)		.00714 (.0272)		.0449** (.0142)	
Fiscal Distress ×Black Driver	−.0683 (.0733)		.0324 (.0455)		−.100 (.0913)		.0163 (.0336)	
Budget Shortfall ×White Driver		.0137 (.0109)		.0203* (.00943)		−.00508 (.00958)		.00810* (.00383)
Budget Shortfall ×Black Driver		−.0300 (.0222)		.00637 (.0112)		−.0389 (.0291)		.00297 (.00836)
Sample	Low Black Stops		High Black Stops		Low Black Stops		High Black Stops	
Agency-Race FE's	X	X	X	X	X	X	X	X
Race-Year FE's	X	X	X	X	X	X	X	X
Demographics	X	X	X	X	X	X	X	X
Stop Reasons	X	X	X	X	X	X	X	X
Arrest Reasons					X	X	X	X
Census×Year FE's		X		X		X		X
N	1,116	1,116	1,002	1,002	815	815	821	821
R^2	.323	.325	.406	.407	.241	.247	.391	.388

Census×Year FE's means pre-2001 local demographics (population, % white, % urban, and % over 65) interacted with year fixed effects.

Notes: Observation is an agency-race-year, where Whites and Blacks are included. *Fiscal Distress* is defined as the log negative revenue change. *Budget Shortfall* is defined as an indicator equaling one if revenue changes were negative last year. ×*Black Driver* and ×*Latino Driver* indicate the interaction between the indicate revenue variable and the respective driver race. Standard errors in parentheses, clustered by agency. $^{+}p<.10$, $^{*}p<.05$, $^{**}p<.01$.

would be low even under significant fiscal pressure. In contrast, if White drivers are not being over-policed, the marginal White driver could more likely be ticketed to raise more revenues.

To look for evidence of this possibility, we produced estimates of the citation and arrest effects, separately by whether the locality is above or below the median of Black driver stop intensity—defined as the number of stops of Black drivers in the previous year, divided by the pre-treatment Black population (year 2000). There is not a difference in the relationship between budgetary concerns and citation rates by Black stop intensity for the continuous measure (columns 1, 3). But we do see a difference for the continuous measure on arrests, and for the discrete measure on citations as well as arrests. Comparing columns 2–4, we see that there is a positive and statistically significant effect on citation rates for White drivers only for areas with a higher previous Black stop intensity. Similarly, comparing columns 5–7 and 6–8, there is a fiscal-pressure effect on arrest rates only in areas with a high Black stop intensity. These results are consistent with an important difference in the revenue potential of the marginal stopped driver, reflecting historical over-policing of Blacks in the United States.

CONCLUSION

The broad contribution of this project is the exploration of how local governments create incentives for law enforcement that contribute to the structure of discriminatory policing. While there is evidence of the relationship between local budget policies and police law enforcement practices, and a separate literature of racial discrimination in policing, this paper is the first to shed light on the interaction of these processes. We find that in response to budget distress, there is greater enforcement activity (ticketing and arrests) for White drivers, but not for non-White drivers. This result offers a different view of discriminatory enforcement than Park (2017), where judges responded to stronger enforcement incentives to administer punishment with greater discrimination: Blacks were more likely to pay a racial punishment tax under pressure-incentive conditions than were Whites (see Kennedy 1998).

There could be many mechanisms underlying the relationship uncovered here. One simple explanation for the marginal change in enforcement behavior is that police are aware of White drivers' greater ability to pay traffic tickets. When higher short-run revenue is necessary, officers shift their limited resources of time to increased targeting of White drivers. Consistent with this idea, we find that the racial differences in enforcement effects are highest in areas where there is a large White-to-Black income ratio. On the other hand, we also have evidence that MO police focus enforcement efforts on Blacks and Latinos in the absence of fiscal distress, despite lower hit rates among these motorists than White drivers and the fact that officers behave consistently with a belief that citations to White drivers generate more revenue. This historical over-policing partly explains our results on fiscal pressures; in areas with historical over-policing of Black drivers, we see a larger re-allocation of tickets from Black to White drivers. An interpretation is that in areas with high Black driver stop intensity, Blacks are already being stopped and cited as much as possible, so the marginal driver is unlikely to produce more revenue.

Future work can shed further light on the factors contributing to the relationship between racial preferences and revenue incentives. Understanding how budget factors affect police discrimination, both in response to short-run fiscal shocks and in the aggregate, may suggest institutional solutions for reducing discrimination. Fiscally pressured enforcement patterns may be valuable evidence of how officers behave in conditions where the incentive to produce race-neutral policing tempers the motivation for racially discriminatory policing. These results raise important questions about the ways tensions in generating fine and fee revenue from poor communities of color may be undergirded by political economy considerations. The broader social consequences of these processes are also uncertain. For example, future work may explore whether racially disparate budget effects have a subsequent impact on crime. The findings presented here highlight the complex relationship between local budgets, policing, and race, as well as much that remains to be studied.

SUPPLEMENTARY MATERIAL

The supplementary material for this article can be found at https://doi.org/10.1017/rep.2020.10.

ACKNOWLEDGMENT

We thank Zoey Chopra, Amanda Fidalgo, Steve Gretz, and Jesus Rodriguez for helpful research assistance. We also thank Peter Enns, Vesla Weaver, attendees of the 2019 Center for American Political Responsiveness conference at the PA State University, and three anonymous referees for their helpful feedback.

NOTES

1 Shoub et al. (2020) consider the importance of institutional motivations for shifts in officer behavior as well, finding that Black drivers are less likely to face discretionary police searches when there is a Black chief of police.

2 John Eligon, "Stopped, Ticketed, Fined: The Pitfalls of Driving While Black in Ferguson," *NY Times*, 6 August 2019.

3 Alternatively, results are also robust to including log expenditures as a control.

4 As mentioned, we obtained annual data for most localities directly from the state of MO. Our main results were similar using data from the state rather than IndFin. With the state data, the RD specification generated larger and more significant effects. The effects with the continuous treatment were less robust.

5 Our results are not robust to using the level of the outcome rather than the first-differenced outcome. But they are robust to using a lagged-outcome-variable design, where we run the regression in levels but include the lagged outcome variable as a regressor without fixed effects.

REFERENCES

Baicker, Katherine, and Mireille Jacobson. 2007. "Finders Keepers: Forfeiture Laws, Policing Incentives, and Local Budgets." *Journal of Public Economics* **91** (11): 2113–36.

Bannon, Alicia, Mitali Nagrecha, and Rebekah Diller. 2010. Criminal Justice Debt: A Barrier to Reentry. Report from Brennan Center for Justice at New York University School of Law, https://www.criminallegalnews.org/media/publications/brennan_center_for_justice_reentry_report_2010.pdf

Baumgartner, Frank R, Derek A Epp, and Kelsey Shoub. 2018. *Suspect Citizens: What 20 Million Traffic Stops Tell Us about Policing and Race*. Cambridge: Cambridge University Press.

Berdejo, Carlos, and Noam Yuchtman. 2013. "Crime, Punishment, and Politics: An Analysis of Political Cycles in Criminal Sentencing." *Review of Economics and Statistics* **95** (3): 741–56.

CEA. 2015. "Fines, Fees and Bail: Payments in the Criminal Justice System that Disproportionately Impact the Poor." White House Council of Economic Advisers Issue Brief.

National Research Council. 2004. *Fairness and Effectiveness in Policing: The Evidence*. Washington, DC: National Academies Press.

Dippel, Christian, and Michael Poyker. 2019. How Common are Electoral Cycles in Criminal Sentencing? Technical report National Bureau of Economic Research.

DOJ. 2015. "Civil Rights Division Report on Ferguson Police Department." U.S. Department of Justice.

Donohue, John J. III, and Steven D. Levitt. 2001. "The Impact of Race on Policing and Arrests." *Journal of Law and Economics* **44** (2): 367–94.

Epp, Charles R, Steven Maynard-Moody, and Donald P Haider-Markel. 2014. *Pulled Over: How Police Stops Define Race and Citizenship*. Chicago: University of Chicago Press.

Fagan, Jeffrey, and Elliott Ash. 2017. "New Policing, New Segregation? From Ferguson to New York." *Georgetown Law Journal* **106**: 33–134.

Fagan, Jeffrey A, Amanda Geller, Garth Davies, and Valerie West. 2009. Race, Ethnicity, and Policing: New and Essential Readings. NYU Press chapter Street Stops and Broken Windows Revisited: the Demography and Logic of Proactive Policing in a Safe and Changing City, pp. 309–48.

Garrett, Thomas A, and Gary A Wagner. 2009. “Red Ink in the Rearview Mirror: Local Fiscal Conditions and the Issuance of Traffic Tickets.” *Journal of Law and Economics* **52** (1): 71–90.
Geller, Amanda, Jeffrey Fagan, Tom Tyler, and Bruce G Link. 2014. “Aggressive Policing and the Mental Health of Young Urban Men.” *American Journal of Public Health* **104** (12): 2321–27.
Goel, Sharad, Maya Perelman, Ravi Shroff, and David Alan Sklansky. 2017. “Combatting Police Discrimination in the Age of Big Data.” *New Criminal Law Review: In International and Interdisciplinary Journal* **20** (2): 181–232.
Goldstein, Rebecca, Michael W Sances, and Hye Young You. 2018. “Exploitative Revenues, Law Enforcement, and the Quality of Government Service.” *Urban Affairs Review* **56** (1): 5–31.
Gordon, Sanford C, and Gregory Huber. 2007. “The Effect of Electoral Competitiveness on Incumbent Behavior.” *Quarterly Journal of Political Science* **2** (2): 107–38.
Grogger, Jeffrey, and Greg Ridgeway. 2006. “Testing for Racial Profiling in Traffic Stops from behind a Veil of Darkness.” *Journal of the American Statistical Association* **101** (475): 878–87.
Gross, Samuel R, and Katherine Y Barnes. 2002. “Road Work: Racial Profiling and Drug Interdiction on the Highway.” *Michigan Law Review* **101**: 651.
Harcourt, Bernard E. 2008. *Against Prediction: Profiling, Policing, and Punishing in an Actuarial Age*. Chicago: University of Chicago Press.
Harmon, Rachel A. 2012. “The Problem of Policing.” *Michigan Law Review* **110**: 761–817.
Harris, Alexes. 2017. *A Pound of Flesh: Monetary Sanctions as Punishment for the Poor*. SAGE Publications Sage UK: London, England.
Harris, David A. 1999. “Stories, the Statistics, and the Law: Why Driving While Black Matters.” *Minnesota Law Review* **84**: 265.
Heriot, Gail. 2017. “Statement of Commissioner Gail Heriot in the U.S. Commission on Civil Rights’ Report on Targeted Fines and Fees Against Communities of Color: Civil Rights and Constitutional Implications.”
Hernández-Murillo, Rubén, and John Knowles. 2004. “Racial Profiling or Racist Policing? Bounds Tests in Aggregate Data.” *International Economic Review* **45** (3): 959–89.
Heymann, Philip B. 2000. “The New Policing.” *Fordham Urban Law Journal* **28**: 407.
Hinton, Elizabeth. 2016. *From the War on Poverty to the War on Crime*. Cambridge: Harvard University Press.
Kennedy, Randall. 1998. *Race, Crime, and the Law*. New York: Vintage Books.
Knowles, John, Nicola Persico, and Petra Todd. 2001. “Racial Bias in Motor Vehicle Searches: Theory and Evidence.” *The Journal of Political Economy* **109** (1): 203–29.
Kubik, Jeffrey D, and John R Moran. 2003. “Lethal Elections: Gubernatorial Politics and the Timing of Executions.” *Journal of Law and Economics* **46** (1): 1–25.
MacDonald, John, Jeffrey Fagan, and Amanda Geller. 2016. “The Effects of Local Police Surges on Crime and Arrests in New York City.” *PLoS ONE* **11** (6): e0157223.
Makowsky, Michael D, and Thomas Stratmann. 2009. “Political Economy at Any Speed: What Determines Traffic Citations?” *American Economic Review* **99** (1): 509–27.
Makowsky, Michael D, Thomas Stratmann, and Alexander T. Tabarrok. 2018. “To Serve and Collect: The Fiscal and Racial Determinants of Law Enforcement.”
Missouri. 2019. “2018 Vehicle Stops Executive Summary, Appendix B.”. URL: https://ago.mo.gov/docs/default-source/public-safety/2018appendixb.pdf?sfvrsn=2.
Park, Kyung H. 2017. “The Impact of Judicial Elections in the Sentencing of Black Crime.” *Journal of Human Resources* **52** (4): 998–1031.
Parker, Karen P., Erin C Lane, and Geoffrey P Alpert. 2010. “Community Characteristics and Police Search Rates.” Race, Ethnicity, and Policing: New and Essential Readings. p. 349.

Persico, Nicola, and Petra Todd. 2006. "Generalising the Hit Rates Test for Racial Bias in Law Enforcement, with an Application to Vehicle Searches in Wichita." *The Economic Journal* **116** (515): F351–67.

Pierson, Emma, Camelia Simoiu, Jan Overgoor, Sam Corbett-Davies, Vignesh Ramachandran, Cheryl Phillips, and Sharad Goel. 2017. "A Large-Scale Analysis of Racial Disparities in Police Stops across the United States." *arXiv preprint arXiv* **1706**: 05678.

The Stanford Open Policing Project. 2019. "The Stanford Open Policing Project." URL: https://openpolicing.stanford.edu/.

Rojek, Jeff, Richard Rosenfeld, and Scott Decker. 2004. "The Influence of Driver's Race on Traffic Stops in Missouri." *Police Quarterly* 7 (1): 126–47.

Rosenfeld, Richard, Jeff Rojek, and Scott Decker. 2011. "Age Matters: Race Differences in Police Searches of Young and Older Male Drivers." *Journal of Research in Crime and Delinquency* **49**: 31–55.

Rowe, Brian. 2010. "Discretion and Ulterior Motives in Traffic Stops: The Detection of Other Crimes and the Revenue from Tickets."

Shoub, Kelsey, Derek A Epp, Frank R Baumgartner, Leah Christiani, and Kevin Roach. 2020. "Race, Place, and Context: The Persistence of Race Effects in Traffic Stop Outcomes." *Journal of Race, Ethnicity, and Politics* Forthcoming.

Sobol, Neil L. 2016. "Lessons Learned from Ferguson: Ending Abusive Collection of Criminal Justice Debt." *University of Maryland Law Journal of Race, Religion, Gender and Class* **15** (2): 293–309.

Soss, Joe, and Vesla Weaver. 2017. "Police are our Government: Politics, Political Science, and the Policing of Race–Class Subjugated Communities." *Annual Review of Political Science* **20**: 565–91.

Tyler, Tom R, and Jeffrey Fagan. 2008. "Legitimacy and Cooperation: Why Do People Help the Police Fight Crime in their Communities." *Ohio State Journal Criminal Law* **6**: 231.

Weaver, Vesla, Gwen Prowse, and Spencer Piston. 2020. "Withdrawing or Drawing In? Political Discourse in Policed Communities." *Journal of Race, Ethnicity, and Politics* Forthcoming.

Wilson, James Q., and George L. Kelling. 1982. "Broken Windows: The Police and Neighborhood Safety." *The Atlantic Monthly* **3**: 29–38.